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Fuzzy monitoring of in-bed postural changes for the prevention of pressure ulcers using inertial sensors attached to clothing

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ABSTRACT

Postural changes while maintaining a correct body position are the most efficient method of preventing pressure ulcers. However, executing a protocol of postural changes over a long period of time is an arduous task for caregivers. To address this problem, we propose a fuzzy monitoring system for postural changes which recognizes in-bed postures by means of micro inertial sensors attached to patients' clothes. First, we integrate a data-driven model to classify in-bed postures from the micro inertial sensors which are located in the socks and t-shirt of the patient. Second, a knowledge-based fuzzy model computes the priority of postural changes for body zones based on expert-defined protocols. Results show encouraging performance in the classification of in-bed postures and high adaptability of the knowledge-based fuzzy approach.

1. Introduction

Pressure ulcers (PUs), as a medical condition, are defined as localized lesions on the skin or underlying dermal tissue, usually appearing over a bone prominence as result of body pressure [1]. The problem of PUs has been on the rise recently and has been described as a *living and alarming epidemic that lives under the sheets of patients at different levels of care*. Consequently, it has been identified as a critical shortcoming in the care of patients [2]. There is a higher prevalence of PUs among adults over 60 years of age (51%) [3]. PUs also appear in patients with limited movement, such as cases of amyotrophic lateral sclerosis or paraplegia. Treatments need to be customized and planned individually for each patient [3]. For PU lesion treatment, intervention methods involve electrical stimulation or ultrasound applied directly to the lesions, making the process painful for patients and expensive for the healthcare system.

Studies on the cost analysis of PUs [4] have concluded that: (i) the cost of treatment increases with the severity of the ulcer because of the longer healing/recovery time; and (ii) this cost includes expenses in material inputs, nursing time and hospitalization charges for the healthcare system, resulting in a significant impact of PUs on the national healthcare system and government budget; therefore, (iii) prevention is the best strategy to address this public health problem [5].

Postural changes are the main method for preventing pressure ulcers [6], whereby patients need to change their position by themselves or with the support of an assistant. Handling these changes of posture, however, can result in excessive physical and emotional stress for caregivers [7]. Given the existence of advanced technologies that aim to improve living conditions, we face the challenge of creating new technological health models to monitor in-bed postural changes for the prevention of PUs. In this work, we present[8] an intelligent system to monitor in-bed posture of patients using wearable inertial sensors as a control and decision-making tool.

The goal of this paper is to develop a data-driven classification for in-bed postures using inertial sensors attached to clothing, which enable us to describe the posture of the patient and orientation of body zones accurately and in a non-invasive way. Second, modeling a secure and flexible approach to compute the priority of postural changes according to a given expert-defined protocol is key to the knowledge-based fuzzy approach.

The remainder of the paper is organized as follows: in Section 2 we detail the review of works related to our proposal; Section 3 presents the proposed methodology to develop a data-driven classification for in-bed postures using inertial sensors attached to clothing; Section 4 introduces the results of a dataset with postural change protocols modelled under our approach. Finally, conclusions and ongoing works are

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discussed in Section 6.

2. Related works

In recent years, academic and industrial research initiatives on smart systems have been developed for healthcare with the aim of supporting future healthcare demands for dependent people to improve their quality of life, reduce healthcare costs, and complement specific medical delivery services [9].

In the scope of this work, despite the impact of the problem, there are not many technology-based works aimed at improving care and monitoring postural changes for PU prevention. We outline the most relevant below.

One of the first developments was proposed in 1995, where the authors [10] defined a pressure sensing device to evaluate the periods during which the skin has been exposed to the measured pressure. Following this initial idea, in [11], the design of a pressure sensor placed between skin and surface was proposed. In [12], an ad-hoc computer application for PU management enabled monitoring of patients suffering from PUs for risk assessment by collecting images and recording PU data, thus favoring the exchange of data between professionals and different levels of care to support decision-making.

Recently, in [13], patient body movement was recorded over time to determine whether the movement of the patient is adequate so as to prevent PUs. However, this patent lacks a description of the methodology to process the data, generate a classification of in-bed postures and configure the protocol of postural changes. In [14], the company *Ortopedia Moverte* developed a product which is described as a rotating wall clock to prevent ulcer formation by allowing the creation of a personalized protocol of postural changes for each patient, by using graphic illustrations of patient positions within a timeframe to be interpreted easily and intuitively. The product [15], a wound analysis application, collects patients' photographs and records, authorized by patients who provide written consent to carry out the treatment. This application defines an objective curve on the evolution of the wounds and also enables consultations among professionals by sharing cases through the application. Another product for patients at risk of suffering PUs [16] is called *integrated system for the prevention of pressure ulcers (smart PUs)*. This application collects information from the patient and applies risk scales to create a personalized guide of preventive actions.

The application *integrated system for the management of wounds* (HELCOS) [17] is a tool that targets both professionals and patients for wound management. The application allows for teleconsultation with experts from other disciplines through a chat function provided for each specific case. The application *pressure ulcer guide* [15] provides information and prevention strategies on pressure ulcers, eschars or wounds. It uses a tool called Braden's Scale to evaluate the risk of pressure ulcers or decubitus eschar.

In [18], the design carried out by Aguagüiña and Granizo had the objective of contributing to patient care during rehabilitation. The system detected body movements and positions using video footage acquired through a Raspberry PI 3 card, receiving image data through a webcam located in front of the patient's bed at a certain distance. In another study conducted by [12], a computer application was presented to standardize the criteria for the prevention, treatment, and follow-up of PUs during patient hospitalization. The system consists of an application used by nurses to collect information in real time, using software capable of interpreting and evaluating the type of control performed on the patient through decision algorithms.

Another noteworthy project is In-bed Pose classification from Pressure Mat Sensors for the Prevention of Pressure Ulcers using Convolutional Neural Networks[19]. In this work, the authors propose a methodology to classify in-bed human positions for the prevention of pressure ulcers using pressure mat sensors. First, they provide a visual representation using fuzzy processing from raw pressure data to gray scale. Second, they define CNN Convolutional Neural Networks models to evaluate the impact of layers on the performance of in-bed posture classification.

In the previous work [20], In the previous work a prototype for monitoring and care of pressure ulcers through an intelligent system based on smart inertial watches was presented. The system detects the position of patients with reduced mobility while in bed, walking or standing, providing data to medical staff and caregivers. In this work, we present a substantial development of the previous prototype by evaluating ad hoc in-bed postures and including a knowledge-based fuzzy approach computing the priority of postural changes in real-time, which enables clinicians to model postural protocols and configure reminders. In order to provide a summary of the strengths and limitations of previous works, we present a table with the most relevant works on technological approaches for PU prevention.

In this work, a new methodology to monitorize in-bed postural changes for PU prevention with inertial sensors attached to clothing is presented. In this way, taking into account all the described literature and previous works, we propose:

- Integration of non-invasive inertial sensors attached to clothing, which send inertial data in real-time. A data-driven model to classify in-bed postures from the micro inertial sensors.
- A knowledge-based fuzzy approach to compute the priority of postural changes in real-time.
- The approach enables clinicians to model postural protocols to configure reminders to be notified in an interpretable and personalized way for injured body zones.

We describe the proposed methodology in detail in the following section.

3. Methodology

In this section, the proposed methodology is presented to classify human in-bed posture for theONE devices were integrated into two socks and one t-shirt, as described in prevention of pressure ulcers using inertial sensors attached to clothing and a knowledge-based fuzzy approach to compute the priority of postural changes. The main components configuring the approach are: (i) inertial sensors attached to clothing, which describe the orientation of patients' body zones in a non-invasive way; (ii) a data-driven model for recognizing in-bed postures, which segments inertial data and classifies the poses; (iii) a knowledge-based fuzzy approach, which computes the priority of postural changes for each body zone according to a defined protocol and the time elapsed from previous in-bed postures; and (iv) a reminder to advise caregivers when the degree of priority of postural change reaches a configurable threshold. In Fig. 1, we show the architecture of components described in the approach, which are detailed in the following sections.

3.1. Inertial sensors attached to clothing

In this section, we describe the micro inertial sensors proposed for sensing in-bed postures, which were attached to patients' clothes in a non-invasive way. In this line, e-textiles [21] have provided a new perspective for wearable non-invasive data sensing from patients. In particular, integrating low-cost micro inertial measurement units [23], which have been demonstrated to describe 105 patient postures [20] or gait speed[22].

For this purpose, we selected the Tactigon ONE device[1] [24] due to its suitable specifications: lightweight (2.5 g device and 6.3 g battery) and small size (5.0 × 1.67 × 0.56 cm). Moreover, the affordable price

[1] Tactigon ONE device https://www.thetactigon.com/products/.

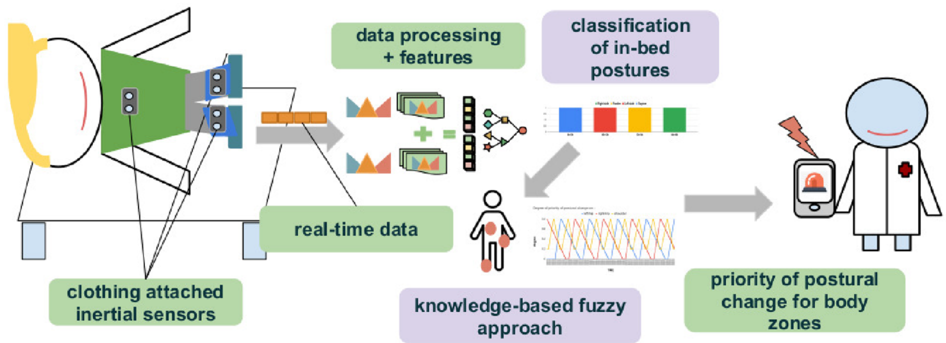

Fig. 1. Architecture of components: (i) inertial sensors attached to clothing, (ii) data-driven model for recognizing in-bed postures, (iii) knowledge-based fuzzy approach to compute the priority of postural changes for body zones, and (iv) a configurable threshold for notifications to caregivers.

Fig. 2. Tactigon ONE: (left) inertial sensor embedded into board; center and (right) Tactigon ONE attached to socks and t-shirt of patient, respectively.

(78 euros) and the open SDK, which enables us to code the board for full configuration (sample rate, communication, sensors, etc.), were the key points in selecting the device.

Three Tactigon ONE devices were integrated into two socks and one t-shirt, as described in Section 2. Acceleration and gyroscope data from the miniature boards were sent under Bluetooth Low Energy (BLE) at a frequency of 20 samples per second.

3.2. Data-driven model for recognition of in-bed postures

Following a formal definition, a sensor s collected data in real time in the form of a pair $\overline{s_i} = \{s_i, t_i\}$, where s_i represents a given measurement and t_i the time-stamp, respectively. Thus, the data stream of the sensor s is defined by $\overline{S_s} = \{\overline{s_0}, ..., \overline{s_i}\}$. In this work, a tri-axial inertial representation (x,y,z) provided three data streams $\overline{S_X}$, $\overline{S_Y}$, $\overline{S_Z}$ from the sensors on acceleration and gyroscope for each inertial device.

Next, a temporal segmentation was defined by a window size W [25] to aggregate the samples $\overline{s_i}$ by a given function $T_t(S_s, t^*)$. The aggregation value defines a feature T_t of the inertial sensors S_s in a given time t^*.

$$T_t\left(S_s, t^*\right) = \bigcup_{s_i}^{\overline{s_i}} s_i,\ t^* - t_i > W,\ t^* \leqslant t_i \quad (1)$$

Therefore, starting from a set of sensors $S = \{S_1, ..., S_s, ..., S_{|S|}\}$ and a set of aggregation functions $T = \{T_1, ..., T_t, ..., T_{|T|}\}$, we defined a total number of features $|S|x|T|$ which describe the segment of sensor data W for each given point of time t^* [26]. Since our model is based on a data-driven supervised approach, the features which describe the inertial sensors are associated with a label $L(t^*)$ for each point of time t^* :

$$T_1(S_1, t^*), ..., T_t(S_s, t^*), ...T_{|T|}(S_{|S|}, t^*) \rightarrow L_l(t^*) \quad (2)$$

where $L_l(t^*)$ defines a discrete value for each point of time t^* between $L = \{L_1, ..., L_l, ..., L_|L|\}$, which identifies a given in-bed posture. In this work, six in-bed postures for the prevention of pressure ulcers were classified: supine, left-side, right-side, Fowler's, supine with bent right leg and supine with bent left leg, which are described in Fig. 3 and represent common in-bed postures for evaluation purposes [27].

Finally, the previously defined features and labels were used to train a data-driven classifier. Among the broad spectrum of models, we focused on light and efficient classifiers, which enable training and evaluation on micro boards in real time under Fog Computing environments[28]. Specifically, in this work, we evaluated three classifiers: K-nearest neighbors (kNN) and support vector machine (SVM) as they provide the best performance in posture classification from inertial sensors [20], together with decision tree (C4.5).

3.3. Knowledge-based fuzzy approach to compute the priority of postural changes

In this section, we detail a knowledge-based fuzzy approach to compute the priority of postural changes from an expert-defined protocol, which is defined by a set of postures L which are changed every time interval T.

First, a given in-bed posture L_l was associated with one or more body zones of the patient $Z = \{Z_1, ..., Z_z ... Z_|Z|\}$ by a membership function $\mu_Z: Z \times L \rightarrow [0, 1]$ which determines a degree of pressure between 0 and 1. For example, for body zone $Z_1 = shoulderblade$ and in-bed postures $L_1 = Supine$, $L_2 = Fowler$, $L_3 = lateralposition$, we defined $\mu_Z(Z_1, L_1) = 1$, $\mu_Z(Z_1, L_2) = 0.5$, $\mu_Z(Z_1, L_3) = 0$. Then, as the postures are recognized in a point of time t^*, a body zone is affected by a pressure degree over time as $Z_z(t^*) = \bigcup_{L_l}^{L} Z_z(L_l(t^*))$.

Second, we applied Fuzzy Temporal Windows (FTW) and fuzzy temporal aggregation [29] over time to compute the degree of pressure of the body zone $Z_z(t^j)$ from previous time-stamps t^j to the current time t^*. FTWs were described straightforwardly according to the distance from the current time t^* to the previous timestamps t^j as $\Delta t^j = t^* - t^j$ using a membership function $\mu_{T_K(\Delta t^j)}$ [30]. Intuitively, a given FTW T_k can be defined by four values $TS(T_{K1}, T_{K2}, T_{K3}, T_{K4})$, which determine a trapezoidal membership function [8] (referred to in Appendix B. In concrete terms, we propose a FTW which covers two time intervals T of postural changes, whose membership function is defined by: $\mu_{T_K(\Delta t^j)} = TS(0, 0, T, 2T)$.

The aggregated degree $Z_z \cup T_k$ of body zone Z_z within temporal window T_K was computed using a fuzzy weighted average [31] (detailed in Appendix A), which is proposed as a suitable representation for high sample rate sensors[29]. The temporal aggregated degree was defined as $Z_z \cup T_k(t^*)$ for each point of time t^*. In Fig. 4, we show an example of the aggregated degree of body zones $Z_1 = shoulder$ and $Z_1 = left/right\ hip$ within the FTW $T_1 = TS(0h, 0h, 2h, 8h)$ per minute t^* over a 24-h timeline using a basic protocol of postures that are changed in two-hour time intervals *supine→right lateral→ fowler → leftlateral*.

Finally, a fuzzy quantifier Q_z [32] was applied in order to provide an interpretable representation of the *priority of postural changes for body zone* Z_z from the aggregated degree of a body zone $Z_z \cup T_k$. A fuzzy quantifier was directly defined to associate both terms by a membership function $\mu_{Q_q}: \left[0, 1\right] \times \left[0, 1\right]$, which should fulfill the principles of monotony and zero-aggregation [33]. In order to model the fuzzy quantifier straightforwardly, the expert only needs to define two or

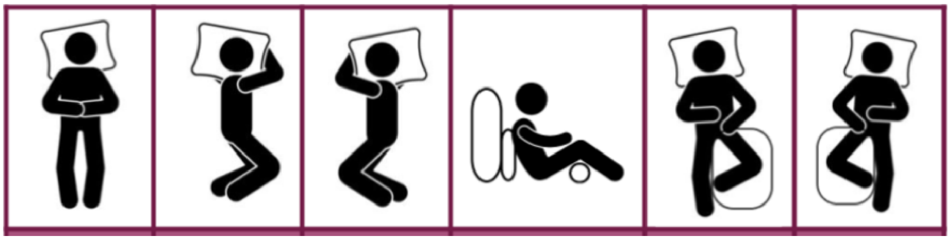

Fig. 3. Classified in-bed postures for the prevention of pressure ulcers (from left to right): supine, left-side, right-side, Fowler's, supine with bent right leg and supine with bent left leg.

more control points [34]. A control point is defined by a 2-tuple $\{t^j, Q_*^j\}$, which associates the aggregation degree of the body zone in a point of time t^j with the degree of priority of postural change Q_*^j modeled by the expert. For the sake of simplicity, the control points were defined by the expert in a beginning t_A and an end point of time t_B for the postural change which affects this body zone, representing minimum and maximum priority degree, respectively. For the remaining values of the temporal aggregated degree of a body zone $Z_z \cup T_k$, a linear interpolation of the control points defines the membership function (detailed in Appendix C) to compute the priority degree of postural change [0, 1]. In Fig. 5, we show an example of the fuzzy quantifier defined by two control points for the body zone *left-hip* whose degrees of priority were defined at the beginning and end of the postural change.

3.3.1. Configurable threshold of postural changes according to caregivers' needs

In the previous Section 3.1, we have described a knowledge-based fuzzy approach to compute the degree of *priority of postural changes for body zone* Z_z from the in-bed postures classified by the inertial sensors. This degree provides interpretable and valuable information to caregivers in order to make the postural changes in a flexible and suitable way.

Moreover, the priority degree for postural changes was defined in the range [0, 1], an $\alpha - cut \in [0, 1]$ to notify the caregiver when the degree surpasses the threshold. We note α_z can be defined for each body zone Z_z; however, for the sake of simplicity, we take α to refer to any or all of them.

So, given the flexibility provided by the knowledge-based fuzzy approach in computing the priority degree for postural changes, the α-cut can be modified over time in order to define a more relaxed or strict threshold and therefore increase or reduce the time between postural changes, depending on the caregiver's time constraints or the patient's wishes. In this way, $\alpha \approx 0$ is associated with the minimum time when postural change affects the body zone, and $\alpha \approx 1$ is associated with maximum recommended time, respectively.

We note the priority degree for postural changes is ultimately modeled by: (i) the fuzzy quantifier defined by experts using controls points, so there is a relation of interpretability between the alerts obtained by α and the fuzzy quantifier Q_q modelling; and (ii) the Fuzzy Temporal Windows, defining a long-term aggregation (usually in a range of hours) of the degree of pressure in a body zone. So, for example, if a postural change has been delayed, the model wisely reduces the time to the next postural change (for the same body zone) since

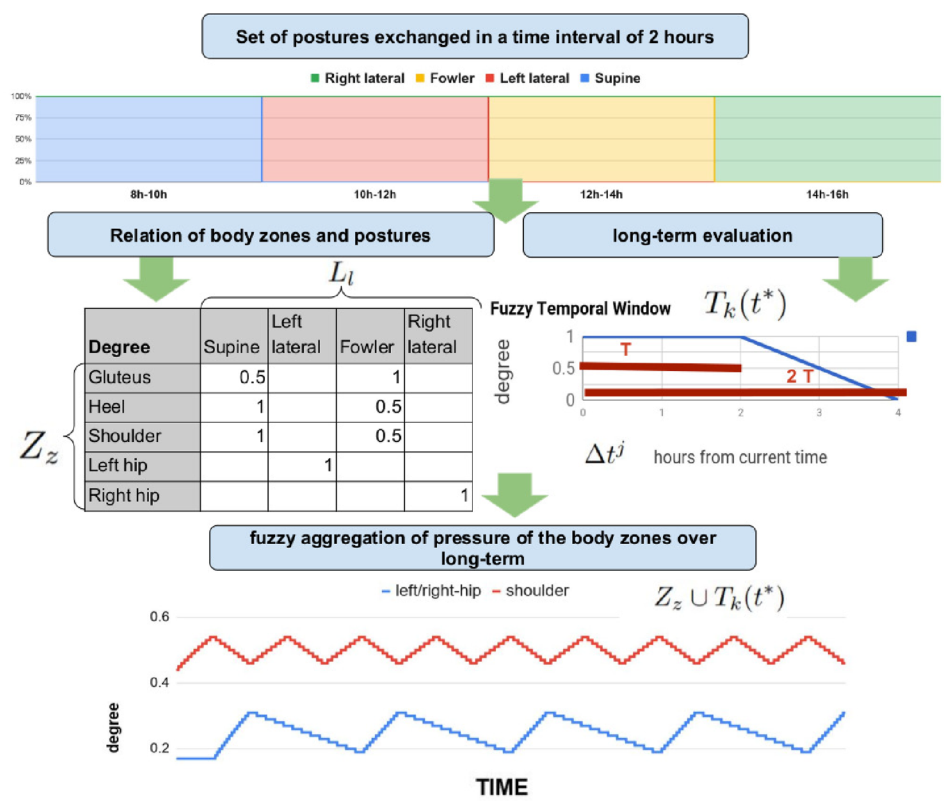

Fig. 4. Fuzzy processing from a basic sequence of postural changes to compute the aggregation degree of pressure of the body zones shoulder and left/right hip over two time intervals T of postural changes.

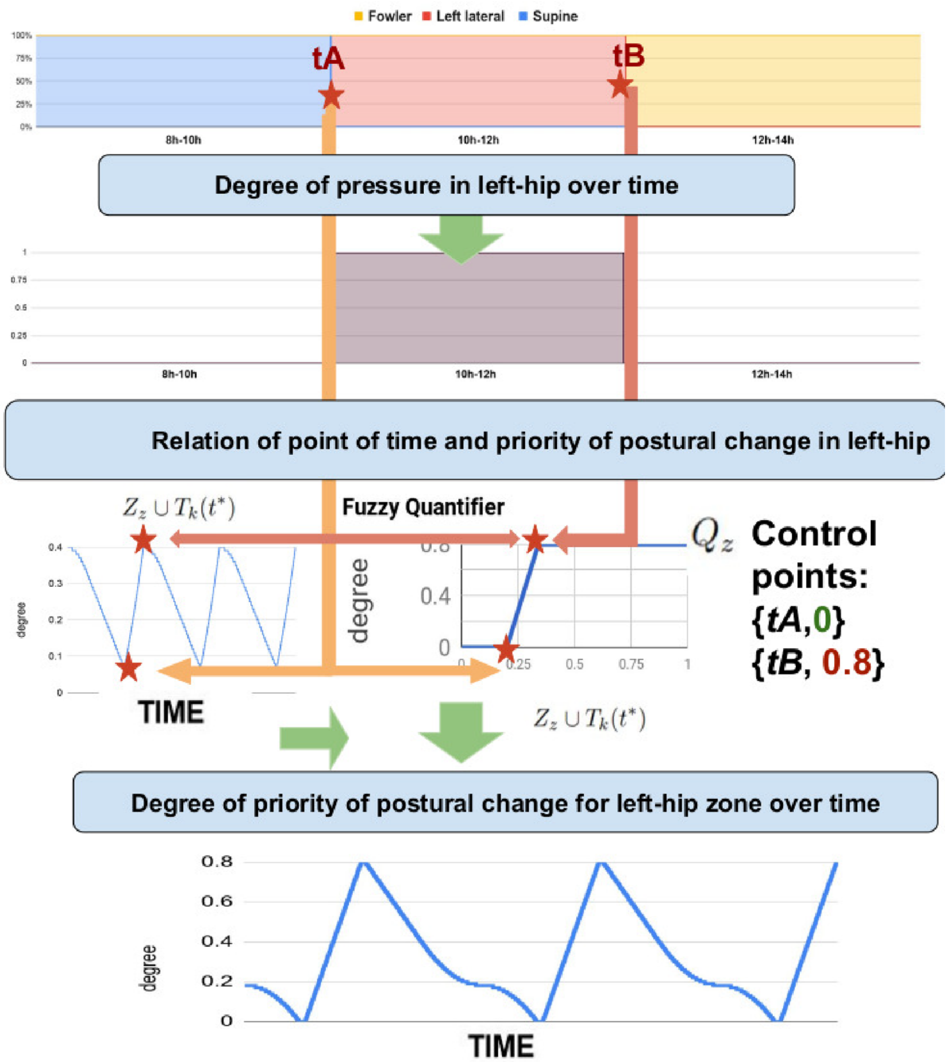

Fig. 5. Fuzzy quantification defined by two control points, defined at the beginning and end of the postural change, to compute the priority degree of postural changes for the body zone. In figure, we show in Fig. 5 the priority degree of postural changes over one day, which evolves according to the postural changes made by caregivers.

threshold α was reached earlier.

In Section 4.2, we detail several in-bed postural protocols which have been modelled using the described methodology.

4. Evaluation

In this section, we describe the results of a dataset and three postural change protocols for PU prevention which have been modelled under our approach.

4.1. Evaluation of in-bed posture recognition by inertial sensors attached to clothing

Firstly, the in-bed posture recognition by inertial sensors attached to clothing was evaluated.

The experimental development of this research study took place at the CEATIC (Centro de Estudios Avanzados en Tecnologías de la Información y de la Comunicación)[2] of the University of Jaen (Spain). Three Tactigon ONE devices were integrated into two socks and one t-shirt, as described in Section 3.1. There were 7 participants (3 male and 4 female). For this case study, the total sample comprised 7 students: 4 women and 3 men with an average age of 24.75 years, an average height of 1.68 m and an average weight of 73 kg. The subjects were students and staff of the University of Jaen Campus. During the experiment, two professionals from Neurobase, a neuro-rehabilitation clinic, participated in the data collection and indicated the postural change protocol for preventing pressure ulcers. They voluntarily signed a consent form to share their data, agreeing to be part of the research effort, understanding the objectives, possible risks, the procedures and benefits. The results of this research study are reported or published for academic purposes, so the names and personal data of the participants have been omitted. In the case study, they wore the clothes with attached sensors in six different in-bed postures: supine, left-side, right-side, Fowler's, supine with bent right leg and supine with bent left leg, which are detailed in Fig. 2. For evaluation purposes, we gathered two datasets of the six in-bed postures for each participant, recording approximately 10 min per posture and 1 h per participant. More than 500,000 samples were collected from inertial sensors in the case study, during which an external observer labelled and timed the postures. The dataset is publicly available in[3] https://github.com/AmsterdamVibes/

[2] UJAmI Smart Lab https://ceatic.ujaen.es/ujami/en/smartlab.

[3] Dataset of In-bed Postures for the Prevention of Pressure Ulcers using

Table 1
Metrics of precision (P), recall (R) and f1-score (F1) with personalized learning in data evaluation.

	SVM			kNN			J48		
	F1-sc	P	R	F1	P	R	F1	P	R
S1	1.00	1.00	1.00	1.00	1.00	1.00	0.37	0.33	0.41
S2	1.00	1.00	1.00	1.00	1.00	1.00	0.59	0.66	0.54
S3	1.00	1.00	1.00	1.00	1.00	1.00	0.49	0.63	0.40
S4	1.00	1.00	1.00	1.00	1.00	1.00	0.55	0.66	0.47
S5	1.00	1.00	1.00	1.00	1.00	1.00	0.36	0.33	0.41
S6	1.00	1.00	1.00	1.00	1.00	1.00	0.60	0.66	0.55
S7	1.00	1.00	1.00	1.00	1.00	1.00	0.61	0.52	0.74
Average	1.00	1.00	1.00	1.00	1.00	1.00	0.51	0.54	0.50

Table 2
Metrics of precision (P), recall (R) and f1-score (F1) with unseen participant learning in data evaluation.

	SVM			kNN			J48		
	F1-sc	P	R	F1	P	R	F1	P	R
S1	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00
S2	1.00	1.00	1.00	1.00	1.00	1.00	0.85	1.00	0.75
S3	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.94
S4	1.00	1.00	1.00	0.99	0.99	0.99	1.00	1.00	1.00
S5	1.00	1.00	1.00	1.00	1.00	1.00	0.87	0.83	0.93
S6	0.97	1.00	0.94	0.99	1.00	0.99	0.96	1.00	0.93
S7	1.00	1.00	1.00	0.99	1.00	0.99	0.69	0.65	0.74
Average	0.99	1.00	0.99	0.99	0.99	0.99	0.91	0.87	0.90

inertial-inbedpostures.

The inertial data were divided into 2.5 s segments [20] and the proposed aggregation functions were: maximal, minimal, average and standard deviation [26]. Three classifiers: K-nearest neighbors (kNN), decision tree (C4.5) and support vector machine (SVM) were evaluated.

Two evaluation methods were carried out. First, an evaluation based on*personalized learning*,where only one dataset per participant was used for training and testing. In this case, one dataset was used for training and the other one for testing (two datasets with six in-bed postures were collected for each participant). Second, an evaluation based on *unseen participant*was analyzed to compare learning and training capabilities using unseen data for each participant. In this case, two datasets for each participant were used as testing data and the other datasets for the rest of the users were used as training data. Both in personalized and non-personalized learning, a leave-one-participant-out cross-validation was performed, obtaining the results described in Tables 1 and 2,respectively. In addition, the confusion matrix for each evaluation and classifier is described inFig. 6.

4.2. Modelling of heterogeneous in-bed postural protocols

Next, we implemented three heterogeneous in-bed postural protocols under the knowledge-based fuzzy approach proposed in this work. The same methodology was followed for both in-bed postural protocols:

- A set of postures L and sequence of postural changes within a time interval T were defined for each protocol.
- A set of body zones Z were related to each posture L_l by a degree of pressure.
- FTW Fuzzy Temporal Windows with a size of two time intervals covered a long-term evaluation of postural changes to compute body zone pressure over time.
- A fuzzy quantifier Q_z was defined to determine an interpretable priority degree of postural changes for each body zone.
- A configurable threshold α was set for the notification to remind the caregiver to change the patient's posture according to their wishes.

4.2.1. Model A: basic postural protocol with two-hour change time intervals

First, a basic postural protocol was defined by 4 in-bed postures: supine, left lateral decubitus, Fowler's and right lateral decubitus, which were changed between two-hour time intervals [35]. Each posture was associated with the body zones of the patients - shoulder, heels, gluteus, left hip and right hip - by a degree of pressure Z_z, which is described in Fig. 7 together with the postures and the cycle of postural changes. Next, two control points, which were defined by the expert in the beginning t_A and end point of time t_B for two-hour long postural changes, determine the degree of priority Q^j_* of postural change for the body zones $\{Q^A\_* = 0, Q^B\_* = 0.8\}$. In this way, the notification threshold for reminders was set to $\alpha - cut = 0.8$ for all body zones, alerting caregivers every two hours if they did not change the patient's posture. The complete configuration for this postural protocol and an example of priority degree for postural changes over one day is shown in Fig. 7.

4.2.2. Model B: Dynamic postural protocol with adaptive change time interval

Second, we defined a dynamic protocol where the elapsed time for postural changes can be partially extended to four hours [36,37]. The same postures and body zones from the previous section were used here; however, in order to facilitate the caregiver's sleep, postural changes at night (from 00 h to 8 h) were extended to four hours while keeping to two hours during the day (from 8 h to 24 h). To model this adaptive protocol, a third control point *tC* was defined in the end point of four-hour postural changes with the maximal priority degree of postural change $Q^C\_* = 1$, obtaining $\{Q^A\_* = 0, Q^B\_* = 0.8, Q^C\_* = 1.0\}$ to be applied at night. To make things simple for caregivers, the configurable notification threshold of reminders was set to $\alpha - cut = 0.8$ during the day and $\alpha - cut = 1.0$ at night to enable knowledge-based fuzzy model dynamic reminders for postural changes between 2 and 4 h respectively. We note that $\alpha - cut \in [0.8, 1]$ can be set by caregivers to compute reminders progressively from 2 to 4 h.

The configuration of parameters of this model together with an example of priority degree for postural changes over 2 days is shown in Fig. 8. We note that in this model we detail 2 days of postural changes to show the four in-bed postures at night.

4.2.3. Model C: postural protocol for preventing pressure over injured body zones

Third, an adapted model for preventing pressure on injured body zones is presented. Among PUs, the sacrum and heels were the most affected locations [38]. As the use of attached inertial sensors enables us to determine the orientation of body zones when they are located appropriately, the particular monitoring of injured areas is made possible. In order to show the recognition of body zone orientation, in this work the following additional in-bed postures were evaluated: supine with bent right leg and supine with bent left leg [27].

In this context, we describe a scenario where the patient suffers an emerging PU in the right heel. In this case, supine posture with bent right leg by knee flexion [39] avoids pressure on the injured area over time. So, in this adapted model, the classic posture *supine* is replaced with *supine with bent right leg* to protect the right heel from pressure caused by the postures described in previous sections. This small change enables a 66% reduction in average pressure per time unit in the given zone, as detailed in Table 3.

(*footnote continued*)
Inertial Sensors Attached to Clothing. https://github.com/AmsterdamVibes/inertial-inbedpostures.

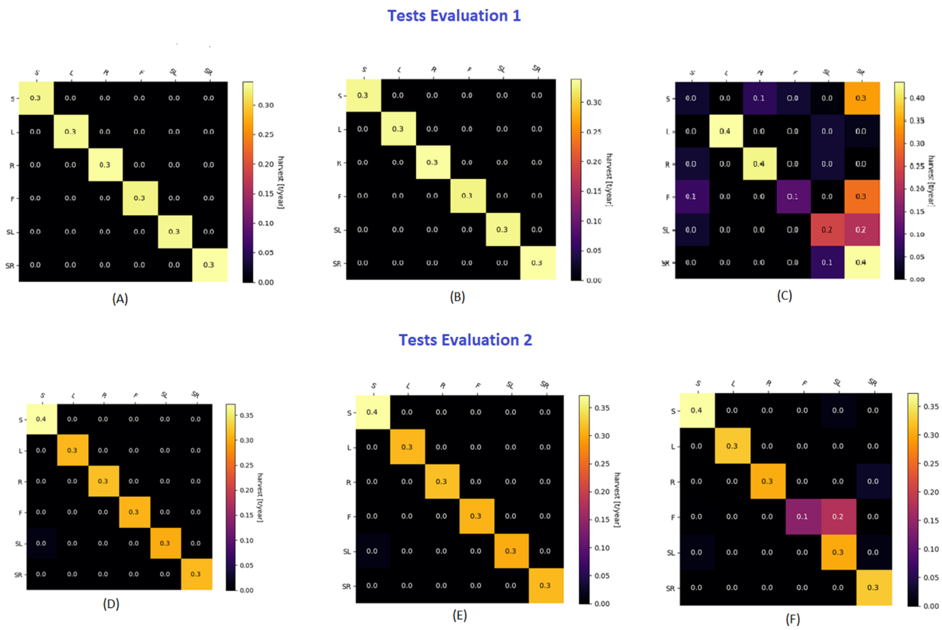

Fig. 6. Confusion matrix: (A) SVM- Support Vector Machine with personalized learning, (B) KNN K-nearest neighbors with personalized learning, (C) C4.5 Decision Tree with personalized learning, (D) SVM Support Vector Machine with unseen participant learning in data evaluation, (E) KNN K-nearest neighbors with unseen participant learning in data evaluation and (F) C4.5 Decision Tree with unseen participant learning in data evaluation.

In order to model the adaptation of the injured body zone to the protocol, three steps were followed. First, the left and right heels were included separately as new body zones, which were then associated with the in-bed postures: supine with bent right leg, left lateral, Fowler's and right lateral by a degree of pressure Z_z. Second, the control points for the injured left heel were decreased to $\{Q^A\_* = 0, Q^B\_* = 0.25, Q^C\_* = 0.5\}$ to represent the need for special attention, determining the priority degree of change in the beginning tA, indicating postural change at two-hours tB and at four-hours tC for the in-bed posture (Fowler's) which affects this body zone (left heel). As in the previous section, the value of the notification threshold for reminders was set to $\alpha - cut = 0.8$ during the day and $\alpha - cut = 1.0$ at night for all body zones except the left heel whose threshold was set to $\alpha\_rightheel = 0.25$ during the day and $\alpha\_rightheel = 0.5$ at night. In Fig. 9, we describe the parameters of this model. We note that the decreasing degree of control points and the

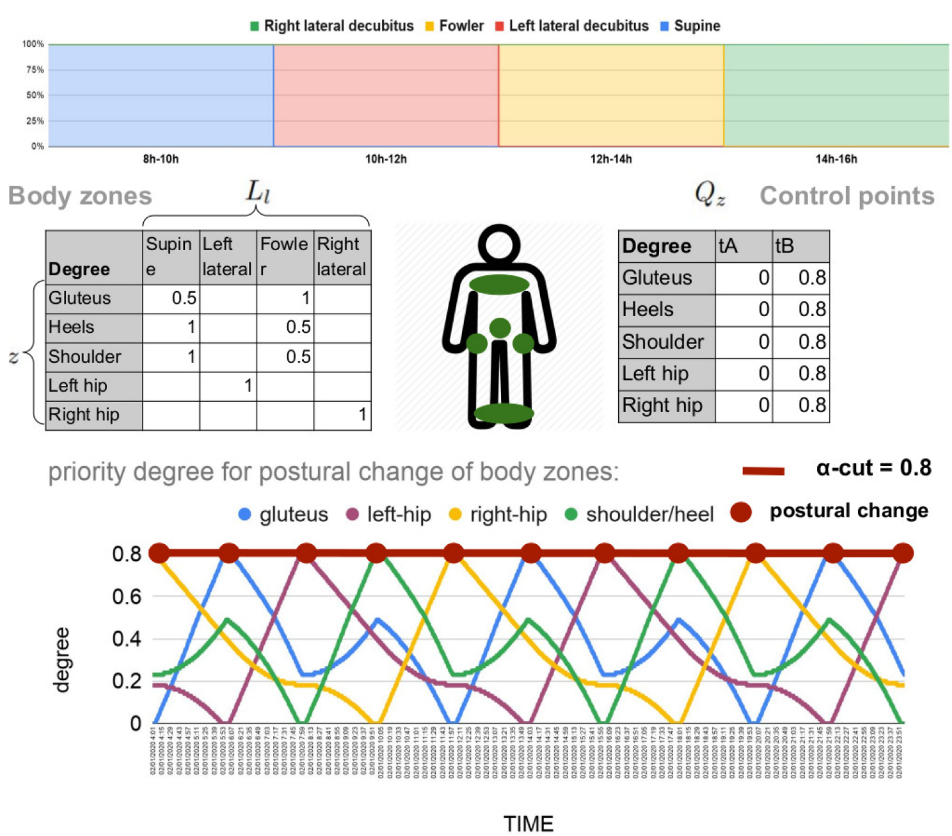

Fig. 7. Basic postural protocol for 4 in-bed postures changed over two-hour time intervals.

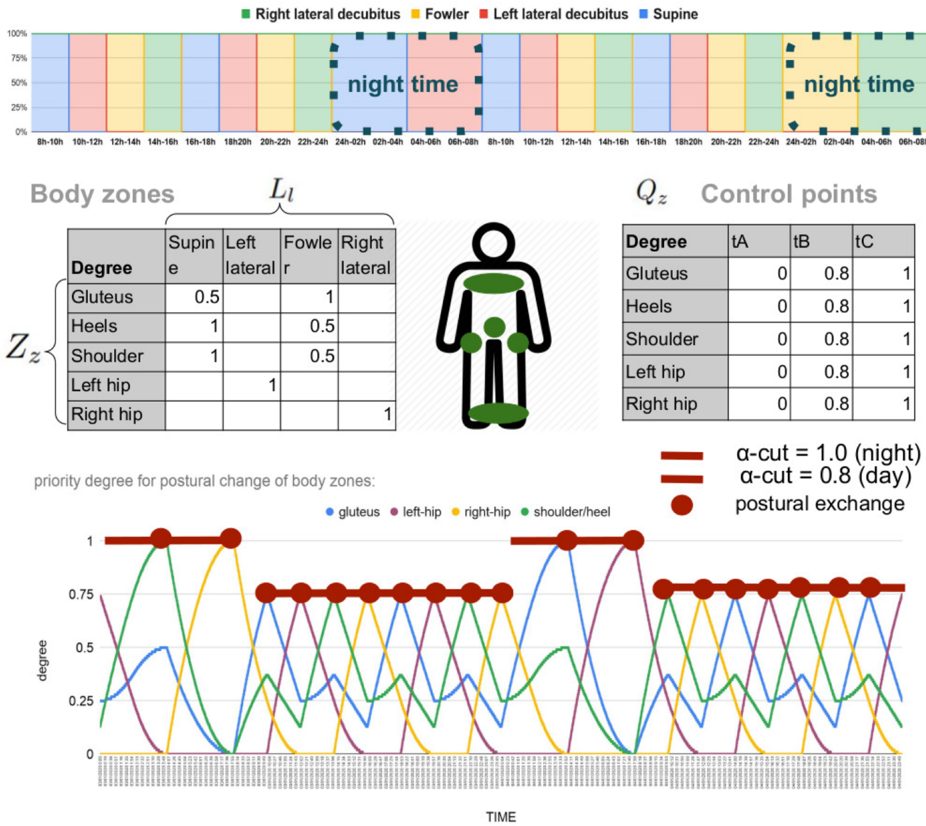

Fig. 8. Dynamic protocol for extending the change time interval from two hours during the day to four hours at night.

Table 3
Average pressure degree per time unit for models A, B and C.

Body zone	Model A/B	Model C
Gluteus	0.38	0.38
Heel right	0.38	**0.13**
Heel left	0.38	0.38
Shoulder	0.38	0.38
Left hip	0.25	0.25
Right hip	0.25	0.25

notification threshold for the left heel would provide caregivers with more interpretable information on this body zone.

5. Discussion: limitations and strengths of deployment in a real-world environment

In this section, we discuss the limitations and strengths of the proposed methodology to be deployed in a real-world environment. First, we detail the strengths identified in real-time monitoring of postural changes for PU prevention using non-invasive inertial sensors:

- We use inertial micro-sensors to detect bed postures, which adhere to patients' clothes in a non-invasive way. The algorithm performs lightweight and optimized processing, which can be integrated into low-cost devices, since it does not require deep learning models. Among the wide spectrum of models, we focus on lightweight and efficient classifiers, which enable real-time training and evaluation on micro-boards in fog computing environments.
- Feature extraction by sliding windows is very agile (2.5 s). This has been shown to be suitable for evaluating inertia activity data and the delay in the response to estimating the classification is negligible. The set of features extracted from the inertial sensors included maximum and minimum values, averages and standard deviation, which have proven to be efficient and suitable to describe inertial sensors in Activity Recognition (AR) and allow the identification and recognition of actions or objectives of the inhabitant. The alert system notifying caregivers does not require a critical response that is sensitive to delays in the communication process of sensors or in the classification of positions. A response time close to some minutes is more than enough and allows work in real time.
- The system does not require customization to obtain high performance, although customization of data is sensitive to decision tree-based classifiers and we observed that the best classification is obtained using customization. So, training data from the patient is key to improve precision performance in real conditions, which would require a shorter phase for pre-training the model.

Having discussed the strengths, it is also necessary to advance in solving certain limitations, issues and open challenges to deployment in real-world conditions:

- The case study carried out in this work was collected from 7 users in controlled environments at the University of Jaen. Although the postural changes of patients at risk of suffering PUs have been guided by rehabilitation experts, future works on patients without mobility will be developed in real conditions according to expert criteria in order to evaluate potential differences between subjects.
- The intelligent system integrates a battery that lasts 48 h. Therefore, support by medical staff is required to replace or recharge the inertial devices every two days and to avoid loss of data.
- One of the relevant points for the success of the project is training medical staff regarding the correct use of the technological devices in order to guarantee correct data collection and obtain the desired results. Staff training and their relationship with new technologies and devices can be a determining factor.

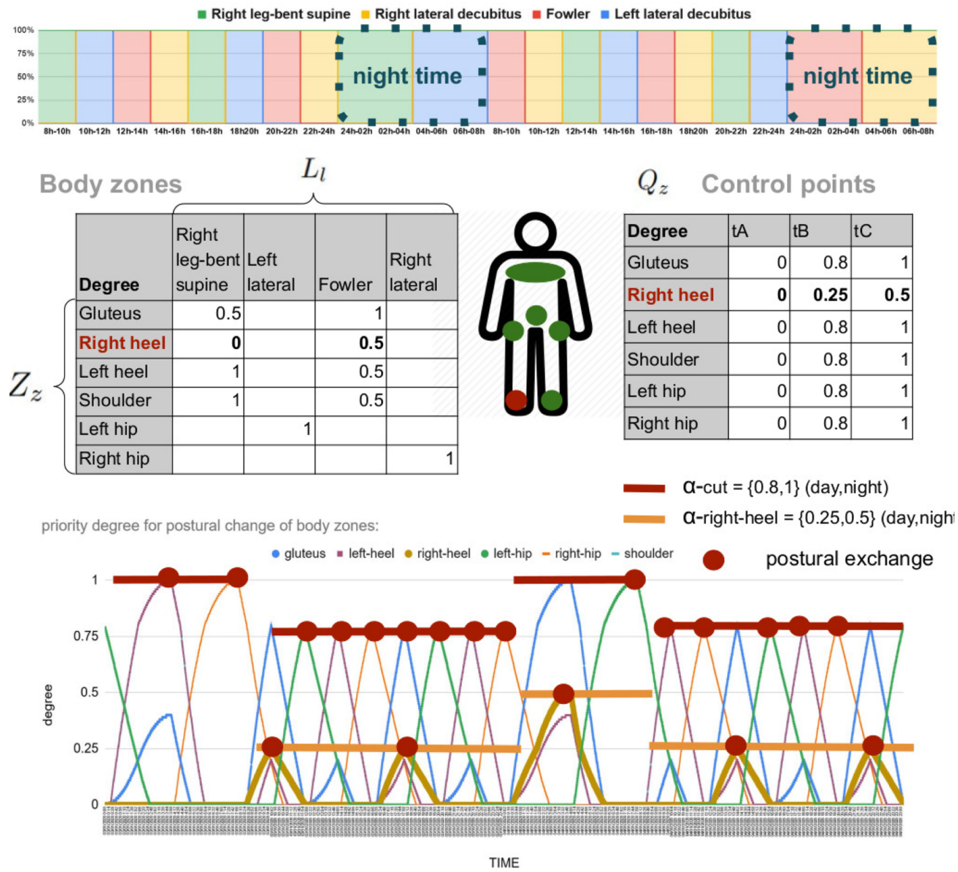

Fig. 9. Adapted protocol for preventing pressure over injured body zones.

- Taking into account that the proposed intelligent system is considered a tool to support medical staff decision-making, it does not present an intervention protocol considering that it does not comply with medical device regulations.
  The device developed in this proposal is a decision support system with many benefits such as:
  - Improving medical staff efficiency: the alert system allows them to monitor patient posture and times in real time.
  - Speeding up the decision-making process: the device generates information that makes it possible to support patient diagnosis and treatment through the data analysis process.
  - Faster problem solving: a specialized team can effectively monitor the study because they are getting data in real time.
  - Convenience: it is a simple device that is easy to install and use by the end user.
  - Improving internal organizational communication: it makes it easy to communicate relevant information with medical staff.
  - Cost reduction for tasks that require decisions: the treatment of PUs can generate high costs for a medical institution; however, use of the device and timely data analysis can prevent the appearance of PUs, shortening patient hospital stays.
  - The developed device does not require any technical knowledge for its use or installation.

5.1. Towards a clinical and technological deployment protocol for PU prevention

Future works could evaluate an inclusive care service model for preventing PUs at home based on the proposed methodology for patients and the involved stakeholders. However, in order to advance in the future deployment of the proposed system in real conditions, involving the health systems, caregivers, clinicians and patients at risk of suffering pressure ulcers, we propose the following actions for the deployment of a PU prevention protocol integrated in the phases outlined below.

Phase 1: Defining the patients at risk of pressure ulcers. This phase consists of the following actions:

- Action 1: Defining and applying a patient assessment tool using the Braden Scale which allows the risk of developing pressure ulcers to be evaluated.
- Action 2: Previous approval from a research ethics committee, determining the number of participants, duration and supervision of clinical trials.
- Action 3: Sharing and signing voluntary consent forms containing personal data, information related to the project, the objective of the research study, the risks, procedures, and benefits of participating in the study.

*Phase 2:*Defining and classifying the patient care model with clinics and caregivers according to the devices designed in the system.

- Action 1: Designing the protocol according to the patient's condition. In this stage, it is important to consider the Braden scale to predict the risk of pressure ulcers, which identifies patients as: high risk, moderate risk or low risk.
- Action 2: Designing the levels of care or protocol according to the patient's score through the evaluation of different aspects such as sensory perception, exposure to moisture, activity, mobility, nutrition, friction and risk of injury.
- Action 3: Defining the type of alerts issued by the devices for each level of care. A notification in the information system will record the

time and position of the patient.

Phase 3: Design and implementation of service provision in the administrative structure of ulcer rehabilitation clinics and health systems. The system will be integrated with the clinical history of the patient to prevent it from being isolated under secure cloud services for health data, which is key in the development of Sensor-Based Health Systems [40].

- Action 1: Modeling the extramural service that incorporates the use of the device and system in the care provided within the institutional portfolio. Designing a medical protocol for use of the device and data collection at home is required for the proper functioning of the intelligent system.
- Action 2: Generation of medical performance indicators, such as reduction of hospital complications, adherence to treatment, service satisfaction, and administrative management indicators.

Phase 4: Training all the actors involved in the care of PU patients. It is relevant to make device manuals and train the medical team and caregivers to guarantee the proper functioning of the proposed system.

Phase 5: Continuing the evaluation and monitoring of the proposed model over 6 months, bearing in mind the previous phases, which is crucial.

- Action 1: Performing tests, applying the designed model, and using the devices created to verify the proper functioning of the system and make the appropriate adjustments.

Phase 6: Evaluation and monitoring the performance of the technological device. Ulcer rehabilitation experts have defined a checklist to validate the device.

- Action 1: Analysis and evaluation of the information obtained during the application of the proposed model.
- Action 2: Readjusting the parameters of the model which define the time and sequence of patient postural changes by clinicians on a personalized basis.

Finally, we note that in this work we propose the implementation of clinical decision support systems for the prevention of PUs. The support devices aim to aid healthcare professionals in decision-making and contribute to improving the interaction between scientific evidence and patient information. The data is presented in an organized way and is available for medical and nursing staff at the appropriate times and in order to improve the quality of care, patient safety and efficiency of hospital processes. This research study proposes a system that works as a clinical support tool, as it allows PU monitoring without interfering in treatment or diagnosis and does not satisfy the requirements of medical devices established by the World Health Organization.

6. Conclusions and ongoing works

In this work, a fuzzy monitoring system for postural changes which recognizes in-bed postures by means of non-invasive inertial sensors attached to patients' clothes has been proposed. First, an evaluation of six in-bed postures by inertial sensors attached to clothing has been performed. The case study shows excellent performance in classifying in-bed postures both in personalizing learning using individualized data for each user and unseen data among users. The performance of the SVM Support Vector Machine classifier is higher than 99%. Second, we have modeled three heterogeneous in-bed postural protocols under the knowledge-based fuzzy approach described in this work. From (i) a basic protocol for 4 in-bed postures changed over two-hour time intervals, we have modeled more complex real and practical contexts: (ii) a dynamic model for extending the change time interval from two hours during the day to four hours at night; and (iii) an adapted protocol for preventing pressure over injured body zones, where the use of attached inertial sensors has successfully described the orientation of patients' heels. Taking into account that the outcome was obtained using a low-cost device, in future work we will analyze the possibility of evaluating the device in other regions or developing countries. Moreover, we are working on attracting interested parties to provide patients so that we can carry out an evaluation of one or several protocols of postural changes within certain segments of patients. Finally,we will explore the application of multi-granular fuzzy linguistic approaches [41] to compare the findings of experts with different criteria on the modeling of postural changes.

CRediT authorship contribution statement

Edna Bernal Monroy: Investigation, Writing - review & editing, Formal analysis. **Aurora Polo Rodriguez:** Resources, Data curation, Formal analysis. **Macarena Espinilla Estevez:** Supervision, Validation, Funding acquisition. **Javier Medina Quero:** Methodology, Conceptualization, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Aggregating Fuzzy Temporal Windows and Terms

For a given body zone Z_z and fuzzy temporal window T_k, we define the fuzzy aggregation $Z\_z \cup T\_k$ in a given current time t^* as:

$$Z\_z \cap T\_k(t^*) = Z\_z(t^j) \cap T\_k(\Delta t^*),\ \Delta t^* = t^* - t^j$$
$$Z\_z \cup T^k(t^*) = \bigcup\_\bar{t}^{j^{t^j < t^*}} Z\_z \cap T\_k(t^*) \tag{A.1}$$

Using weighted average [29] as an operation to model the t-norm and co-norm, we obtain:

$$Z\_z \cup T\_k(t^*) = \frac{1}{\sum\_{t^{j \in t^j < t^*}} T\_k(\Delta t^j)} \sum\_{t^{j \in t^j < t^*}} Z\_z(t^j) \times T\_k\left(\Delta t^j\right) \in \left[0, 1\right. \tag{A.2}$$

Appendix B. Representation of fuzzy temporal windows using trapezoidal membership functions

Each FTW T_k is described by a trapezoidal function based on the time interval from a previous time t^j to the current time t^*: $T\_k(\Delta t^j)[l\_1, l\_2, l\_3, l\_4]$ and a fuzzy set characterized by a membership function whose shape corresponds to a trapezoidal function. The well-known trapezoidal membership functions are defined by a lower limit l_1, an upper limit l_4, a lower support limit l_2, and an upper support limit l_3 (refer to Eq. (B.1)):

$$TS(x)\left[l\_1, l\_2, l\_3, l\_4\right] = \begin{cases} 0 & x \leqslant l\_1 \\ (x - l\_1)/(l\_2 - l\_1) & l\_1 < x < l\_2 \\ 1 & l\_2 \leqslant x \leqslant l\_3 \\ (l\_4 - x)/(l\_4 - l\_3) & l\_3 < x < l\_4 \\ 0 & l\_4 \leqslant x \end{cases} \tag{B.1}$$

Appendix C. Representation of fuzzy quantifiers using control points

A control point is defined by a 2-tuple $Q^j = \{t^j, Q^j\_*\}$, where t^j is a point of time and Q^j_* is the degree of priority of postural change defined by the expert.

First, we compute the aggregation degree of the body zone $Z\_z \cup T\_k$ in the point of time t^j obtaining a new 2-tuple $Q'^j = \{d^j, r^j\} = \{Z\_z \cup T\_k(t^j), Q^j\_*\}$.

Next, a linear interpolation $L(x, Q'^j)$of the control points defines the membership function $\mu\_Q\_q = L(\{Z\_z \cup T\_k(t^j), Q^j)$ which is defined from the domain $Z\_z \cup T\_k \in [0, 1]$ to the range of priority degree [0, 1]

$$L(x) = \begin{cases} 0 & x \leqslant d^0 \\ r^i + (x - d^i)/(r^i - d^i) & d^i x \leqslant d^{i+1} \\ 1 & d^N \leqslant x \end{cases} \tag{C.1}$$

References

[1] M.S.P. Social, Herramientas para promover la estrategia de la seguridad del paciente en el sistema obligatorio de garantía de calidad de la atencion en salud, Ministerio de salud gobierno de Colombia 65 (2007) 60–64.
[2] P.L. Pancorbo-Hidalgo, F.P. García-Fernández, J.-E. Torra i Bou, J. Verdú Soriano, J. J. Soldevilla-Agreda, Epidemiología de las úlceras por presión en espa na en 2013: 4. estudio nacional de prevalencia, Gerokomos 25 (2014) 162–170.
[3] U. Nations, Department of economic and affairs undesa. Population ageing, 2006.
[4] X.-L. Zuo, F.-J. Meng, A care bundle for pressure ulcer treatment in intensive care units, Int. J. Nurs. Sci. 2 (2015) 340–347.
[5] L. Demarré, A. Van Lancker, A. Van Hecke, S. Verhaeghe, M. Grypdonck, J. Lemey, L. Annemans, D. Beeckman, The cost of prevention and treatment of pressure ulcers: a systematic review, Int. J. Nurs. Stud. 52 (2015) 1754–1774.
[6] S. Sprigle, S. Sonenblum, Assessing evidence supporting redistribution of pressure for pressure ulcer prevention: a review, J. Rehabil. Res. Dev. 48 (2011) 203–213.
[7] T. Defloor, K. Vanderwee, T. Dassen, Pressure ulcer prevention and repositioning, in: Science and Practice of Pressure Ulcer Management, Springer, Basel, Switzerland, 2006, pp. 67–73.
[8] J. Medina-Quero, S. Zhang, C. Nugent, M. Espinilla, Ensemble classifier of long short-term memory with fuzzy temporal windows on binary sensors for activity recognition, Expert Syst. Appl. 114 (2018) 441–453.
[9] P. Sundaravadivel, E. Kougianos, S.P. Mohanty, M.K. Ganapathiraju, Everything you wanted to know about smart health care: Evaluating the different technologies and components of the internet of things for better health, IEEE Consum. Electron. Mag. 7 (2017) 18–28.
[10] D.W. Kress, US Patent 4,554,930, U.S. Patent and Trademark Office, Washington, DC, 1985.
[11] J. Rosser, G. Scott, G. Scott, US Patent App. 10/861,701, 2005.
[12] O.B. Yá nez, J.R. Arrieta, M.I.B. Bafaluy, J.J.C. Aguirre, Evaluación e impacto del uso de las tecnologías de la información y comunicación para la gestión clínica y seguimiento compartido y consensuado de las úlceras por presión, Revista Espa nola de Geriatría y Gerontología 50 (2015) 179–184.
[13] P. Kaikenger, R.L. Williamson, T.S. Ventrola, D.R. Tallent, I.L.S. Coleman,. Stebbins, K L, C. LAI, US Patent App. 15/822,532, 2018.
[14] O. Moverte, Reloj control cambios posturales referencia 3948, 2006. Available online: https://www.moverte.com/equipamiento-sociosanitario/3948-reloj-control-cambios-posturales.html.
[15] D. Gneaupp, Grupo nacional para el estudio y asesoramiento en úlceras por presión, Revisión de febrero de 2019 (2003).
[16] g. d. C. Sociedad para el desarrollo regional de Cantabria, Smart upp, sistema undesa. population ageing 2006 para la prevención de Úlceras por presión, 2019. Online: https://www.smartupp.es/ (accessed on 10 March 2019).
[17] Helcos, App: Sistema integrado para el manejo de heridas (helcos), 2019. Available online: https://helcos.net/users/login.
[18] A. Pilataxi, H. Daniel, Sistema electrónico para asistir a pacientes en proceso de rehabilitación de úlceras por presión (bachelor's thesis universidad técnica de ambato. facultad de ingeniería en sistemas electrónica e industrial. carrera de ingeniería en electrónica y comunicaciones), 2018.
[19] C.N. Aurora Polo Rodrıguez, David Gil, J. Medina, In-bed pose classification from pressure mat sensors for the prevention of pressure ulcers using convolutional neural networks (2018) 11.
[20] E.B. Monroy, D.Z. Romero, M.E. Estévez, F. Cruciani, I. Cleland, C. Nugent, J. Medina-Quero, Intelligent system for the prevention of pressure ulcers by monitoring postural changes with wearable inertial sensors, in: Multidisciplinary Digital Publishing Institute Proceedings, vol. 31, 2019, p. 79.
[21] A. Fleury, M. Sugar, T. Chau, E-textiles in clinical rehabilitation: a scoping review, Electronics 4 (2015) 173–203.
[22] F. Lin, A. Wang, Y. Zhuang, M.R. Tomita, W. Xu, Smart insole: A wearable sensor device for unobtrusive gait monitoring in daily life, IEEE Trans. Industr. Inf. 12 (2016) 2281–2291.
[23] K. Jedrasiak, K. Daniec, A. Nawrat, The low cost micro inertial measurement unit, in: 2013 IEEE 8th Conference on Industrial Electronics and Applications (ICIEA), IEEE, 2013, pp. 403–408.
[24] Tactigon, The Tactigon ONE, www.thetactigon.com/, 2020 [Online; accessed 1-02-2020].
[25] O. Banos, J.-M. Galvez, M. Damas, H. Pomares, I. Rojas, Window size impact in human activity recognition, Sensors 14 (2014) 6474–6499.
[26] M. Espinilla, J. Medina, A. Salguero, N. Irvine, M. Donnelly, I. Cleland, C. Nugent, Human activity recognition from the acceleration data of a wearable device. which features are more relevant by activities?, in: Multidisciplinary Digital Publishing Institute Proceedings, vol. 2, 2018, p. 1242.
[27] M.B. Pouyan, J. Birjandtalab, M. Heydarzadeh, M. Nourani, S. Ostadabbas, A pressure map dataset for posture and subject analytics, 2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), IEEE (2017) 65–68.
[28] M.Á. López Medina, M. Espinilla, C. Paggeti, J. Medina Quero, Activity recognition for iot devices using fuzzy spatio-temporal features as environmental sensor fusion, Sensors 19 (2019) 3512.
[29] J. Medina, L. Martinez, M. Espinilla, Subscribing to fuzzy temporal aggregation of heterogeneous sensor streams in real-time distributed environments, Int. J. Commun. Syst. 30 (2017) e3238.
[30] J. Medina, M. Ruiz-Lozano, M. Delgado, A. Vila, A fuzzy temporal rule-based system for handling the nursing process on mobile devices, Expert Syst. Appl. 39 (2012) 10479–10488.
[31] W. Dong, F. Wong, Fuzzy weighted averages and implementation of the extension principle, Fuzzy Sets Syst. 21 (1987) 183–199.
[32] L.A. Zadeh, A computational approach to fuzzy quantifiers in natural languages, in: Computational linguistics, Elsevier, 1983, pp. 149–184.
[33] M.D. Peláez-Aguilera, M. Espinilla, M.R. Fernández Olmo, J. Medina, Fuzzy linguistic protoforms to summarize heart rate streams of patients with ischemic heart disease, Complexity 2019 (2019).
[34] J. Medina, M. Espinilla, Á. García-Fernández, L. Martínez, Intelligent multi-dose medication controller for fever: From wearable devices to remote dispensers, Comput. Electr. Eng. 65 (2018) 400–412.
[35] K.D. Duncan, Preventing pressure ulcers: the goal is zero, The, Joint Commiss. J. Quality Patient Saf. 33 (2007) 605–610.

[36] C. Searle, F. McInerney, Nurses' decision-making in pressure area management in the last 48 hours of life, Int. J. Palliative Nurs. 14 (2008) 432–438.
[37] M. Clark, Repositioning to prevent pressure sores–what is the evidence?, Nursing Standard (through 2013) 13 (1998) 58.
[38] Y. Yoshikawa, N. Maeshige, M. Sugimoto, M. Uemura, M. Noguchi, H. Terashi, Positioning bedridden patients to reduce interface pressures over the sacrum and great trochanter, J. Wound Care 24 (2015) 319–325.
[39] F. Collins, Sitting: pressure ulcer development, Nursing Standard (through 2013) 15 (2001) 54.
[40] M.D. Peláez, M. López-Medina, M. Espinilla, J. Medina-Quero, Key factors for innovative developments on health sensor-based system, in: International Conference on Bioinformatics and Biomedical Engineering, Springer, 2017, pp. 665–675.
[41] F.J. Cabrerizo, J.A. Morente-Molinera, W. Pedrycz, A. Taghavi, E. Herrera-Viedma, Granulating linguistic information in decision making under consensus and consistency, Expert Syst. Appl. 99 (2018) 83–92.